Argonne
NATIONAL LABORATORY

... for a brighter future

# Weather Forecast-Based Optimization of Integrated Energy Systems

*Mihai Anitescu, Argonne National Laboratory*

*INFORMS San Diego, 2009*

*With Victor Zavala, Emil Constantinescu, and Ted Krause, Argonne National Laboratory*

U.S. Department of Energy

UChicago ▸ Argonne LLC

# Outline

**Objective:** **Integrative Study of Weather Forecast-Based Optimization**

**Questions: 1: Can I do a good job in modeling weather uncertainty?**

**2: Is it worth it (economically)?**

**Research Problem**

- **Interaction Weather Conditions - Operations**

**On-Line Stochastic Optimization**

- **Need for Consistent Uncertainty Information**

**Uncertainty Quantification**

- **Time-Series vs. Physics-Based Models**

**Case Studies**

- **Photovoltaic-$H_2$, Building Thermal Control**

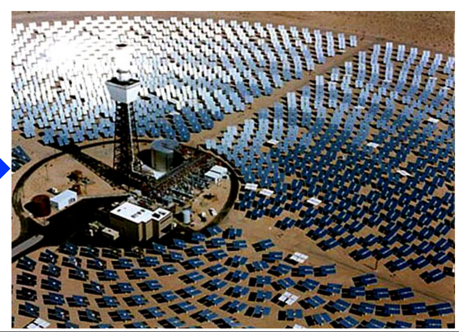
**Conclusions and Future Work**

# Research Problem

# Research Problem—Why?

- **Operation of 90% of Energy Systems is Affected by Ambient Conditions**
  - **Power Grid Management:** **Predict Demands** *(Douglas, et.al. 1999)*
  - **Power Plants:** **Production Levels** *(General Electric)*
  - **Petrochemical:** **Heating and Cooling Utilities** *(ExxonMobil)*
  - **Buildings:** **Heating and Cooling Needs** *(Braun, et.al. 2004)*
  - **Next Generation:** **Wind + Solar + Fossil** *(Beyer, et.al. 1999)*
- **Efficiency (Waste) Becoming a Major Concern: Focus on management, not only design**

**Benefits of Anticipating Weather Conditions?**

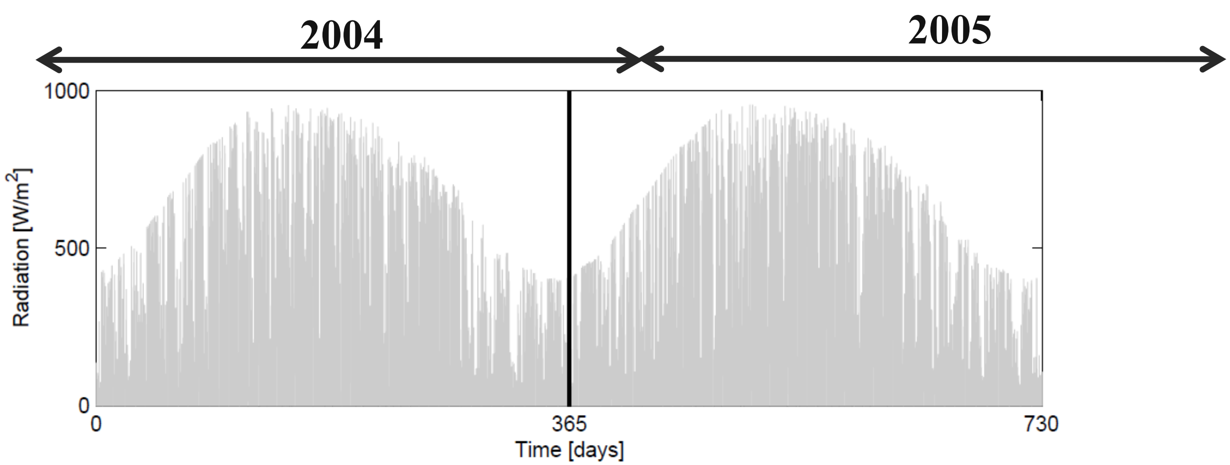


# Research Problem

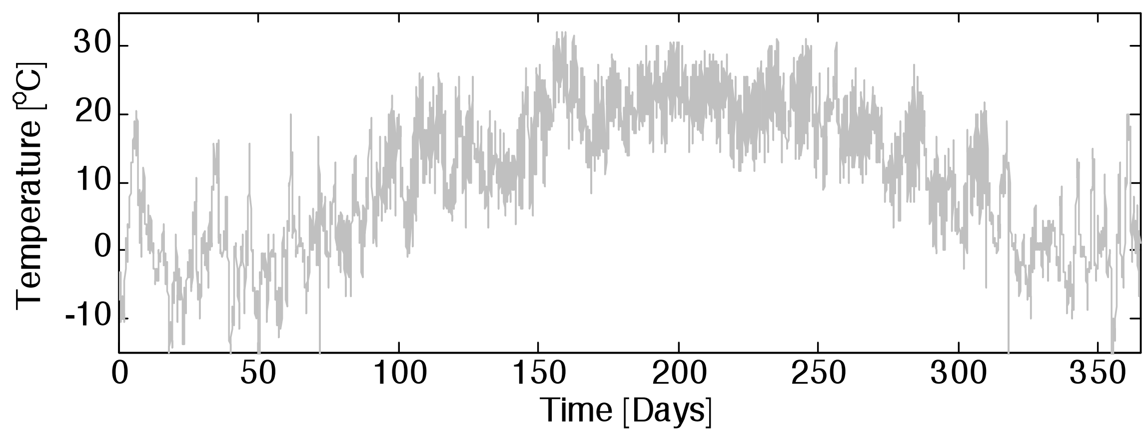
**Weather Conditions (Temperature, Radiation, Wind Speed, Humidity …)**

- **Complex Physico-Chemical Phenomena, Spatio-Temporal Interactions**
- **Inherently Periodic (Day-Night, Seasonal)**

**Total Ground Solar Radiation**
**Chicago, IL**



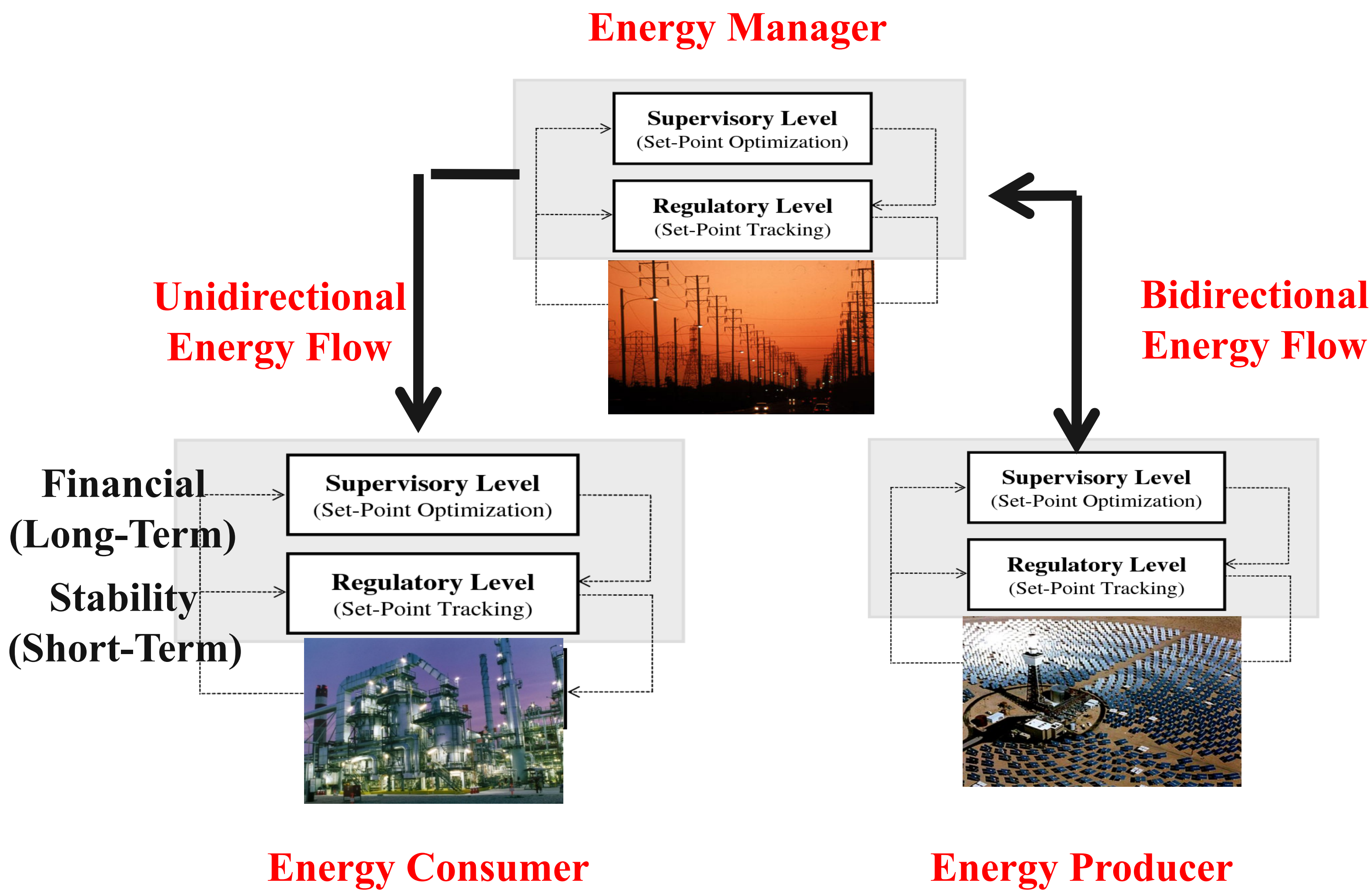

**Ambient Dry-Bulb Temperature**
**Pittsburgh, PA**




**How to Handle Uncertainty?**

# On-Line Stochastic Optimization

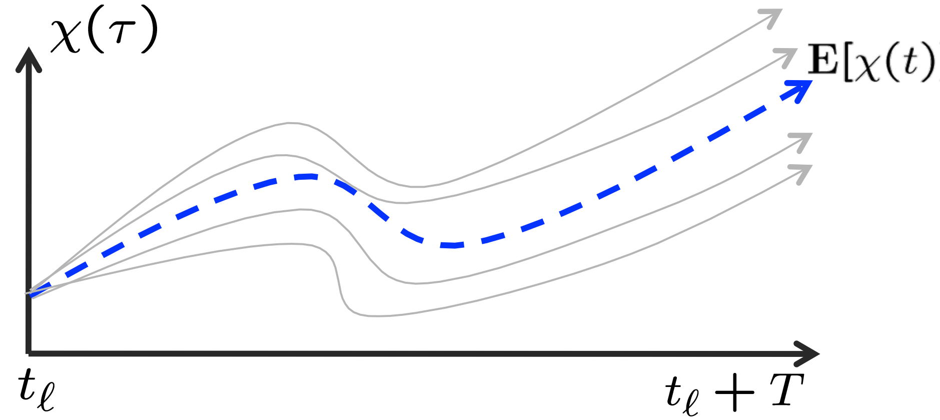
# Hierarchical Operations




**Optimization Traditionally <u>Reactive</u>, Uncertainty Handling Non-Systematic**

# Receding Horizon Optimization

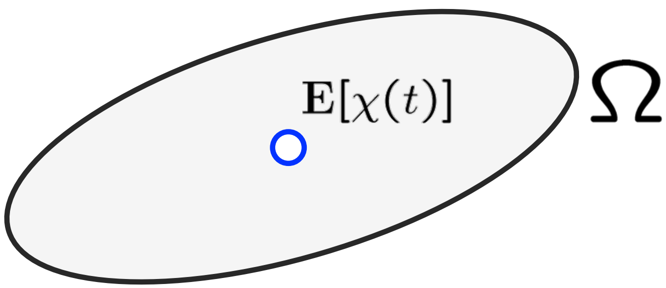
**Benefits:** **Accommodate Forecasts, Constraint Handling, Financial Objectives, Complex Models**




## Deterministic

$$\min_{u(t)} \quad \int_{t_\ell}^{t_{\ell+N}} \varphi(z(t), y(t), u(t), \mathbf{E}[\chi(t)])dt$$

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}(z(t), y(t), u(t), \mathbf{E}[\chi(t)]) \\ 0 &= \mathbf{g}(z(t), y(t), u(t), \mathbf{E}[\chi(t)]) \\ 0 &\geq \mathbf{h}(z(t), y(t), u(t), \mathbf{E}[\chi(t)]) \\ z(0) &= x_\ell \end{aligned}$$

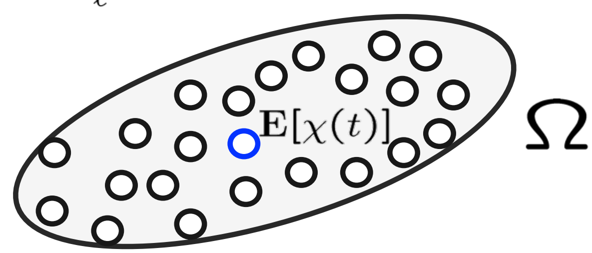



## Stochastic

$$\min_{u(t)} \quad \mathop{\mathbf{E}}_{\chi(t)\in\Omega} \left[ \int_{t_\ell}^{t_{\ell+N}} \varphi(z(t), y(t), u(t), \chi(t))dt \right]$$

$$\left.\begin{aligned} \frac{dz}{dt} &= \mathbf{f}(z(t), y(t), u(t), \chi(t)) \\ 0 &= \mathbf{g}(z(t), y(t), u(t), \chi(t)) \\ 0 &\geq \mathbf{h}(z(t), y(t), u(t), \chi(t)) \end{aligned}\right\} \quad \forall \chi(t) \in \Omega$$

$$z(0) = x_\ell$$




**Complexity (Solution Time)**

**1,000 – 10,000 Differential-Algebraic Equations**

**100-1000 Scenarios**

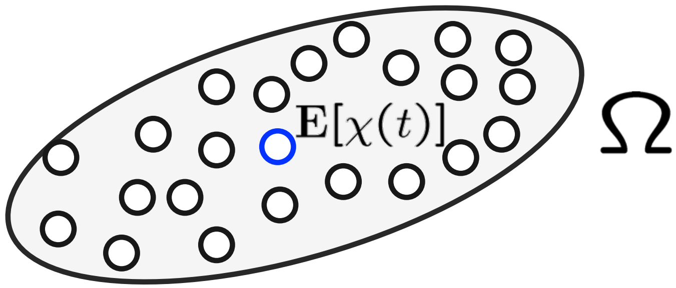
# Stochastic Dynamic Optimization

## Solution Strategies

- **Dynamic Programming, Taylor Series:** Handling Constraints and Nonlinearity Cumbersome
- **Polynomial Chaos:** Dense Optimization, Multivariable Quadrature
- **Sample Average Approximation (SAA):** Sparse Optimization, Constraints, General Framework

$$\min_{u(t)} \quad \mathbf{E}_{\chi(t)\in\Omega}\left[\int_{t_\ell}^{t_{\ell+N}} \varphi(z(t),y(t),u(t),\chi(t))dt\right]$$

$$\left.\begin{aligned}
\frac{dz}{dt} &= \mathbf{f}(z(t),y(t),u(t),\chi(t)) \\
0 &= \mathbf{g}(z(t),y(t),u(t),\chi(t)) \\
0 &\geq \mathbf{h}(z(t),y(t),u(t),\chi(t)) \\
z(0) &= x_\ell
\end{aligned}\right\} \forall \chi(t) \in \Omega$$

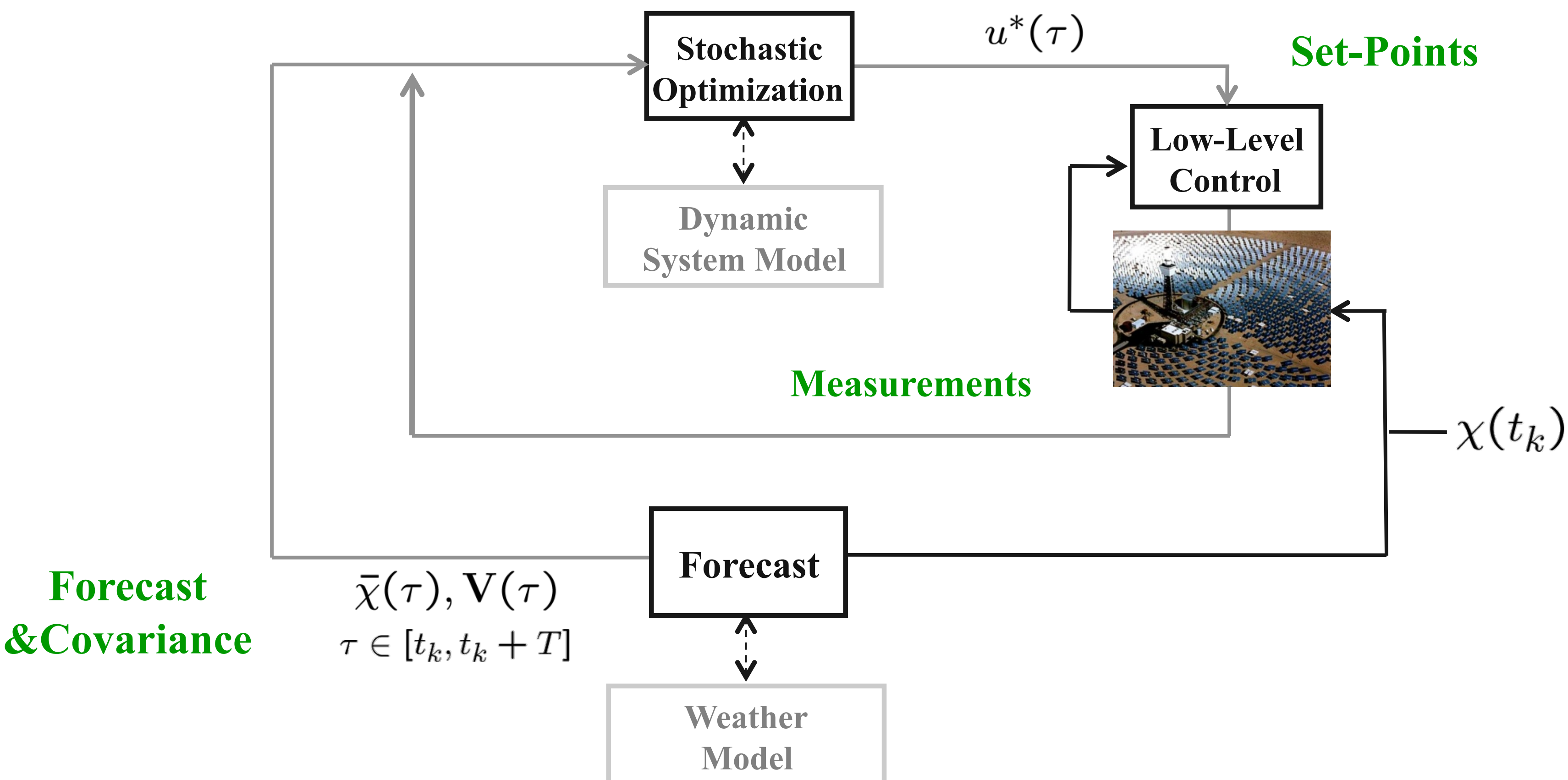



**Nonlinear Programming:** Exploit Fine and Coarse Structures at Linear Algebra Level

$$\begin{aligned}
\min_{\mathbf{u}} \quad & \frac{1}{S}\sum_{k=1}^{S} \varphi(z_k,y_k,\mathbf{u},\chi_k) \\
\text{s.t.} \quad & \mathbf{c}(z_k,y_k,\mathbf{u},\chi_k) = 0 \\
& \mathbf{h}(z_k,y_k,\mathbf{u},\chi_k) \leq 0 \\
& k = 1,...,S
\end{aligned}$$

$$\begin{bmatrix}
\mathbf{K}_1 & & & & Q_1 \\
& \mathbf{K}_2 & & & Q_2 \\
& & \ddots & & \vdots \\
& & & \mathbf{K}_S & Q_S \\
Q_1^T & Q_2^T & \dots & Q_S^T & D_{\mathbf{u}}
\end{bmatrix}
\begin{bmatrix}
\Delta s_1 \\ \Delta s_2 \\ \vdots \\ \Delta s_S \\ \Delta \mathbf{u}
\end{bmatrix}
= -
\begin{bmatrix}
r_1 \\ r_2 \\ \vdots \\ r_S \\ r_{\mathbf{u}}
\end{bmatrix}$$

# Basic Operational Setting



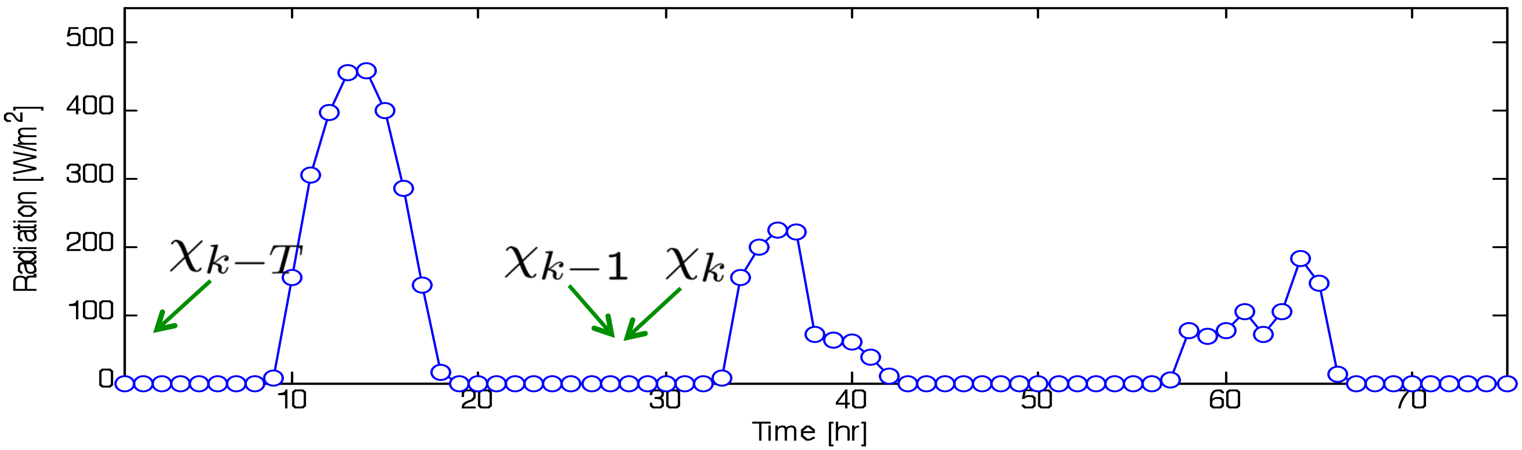

**Quantifying Uncertainty Key Enabler**

# Uncertainty Quantification

# Uncertainty Quantification

## Quantifying Model Uncertainty (Data-Based (Time-Series) vs. Physics-Based)

**Solar Radiation Forecast with Gaussian Process (GP) Modeling** *Zavala & A, 2008*




**1. Input-Output Data Sets:** $\mathbf{Y}_j := \chi_k \qquad \mathbf{X}_j := [\chi_{k-1},\ \chi_{k-T}]$

**2. Covariance Structure :** $\mathbf{V}(\mathbf{X}_j, \mathbf{X}_i, \eta) := \eta_0 + \eta_1 \cdot \exp\left(-\frac{1}{\eta_2}\|\mathbf{X}_j - \mathbf{X}_i\|^2\right)$

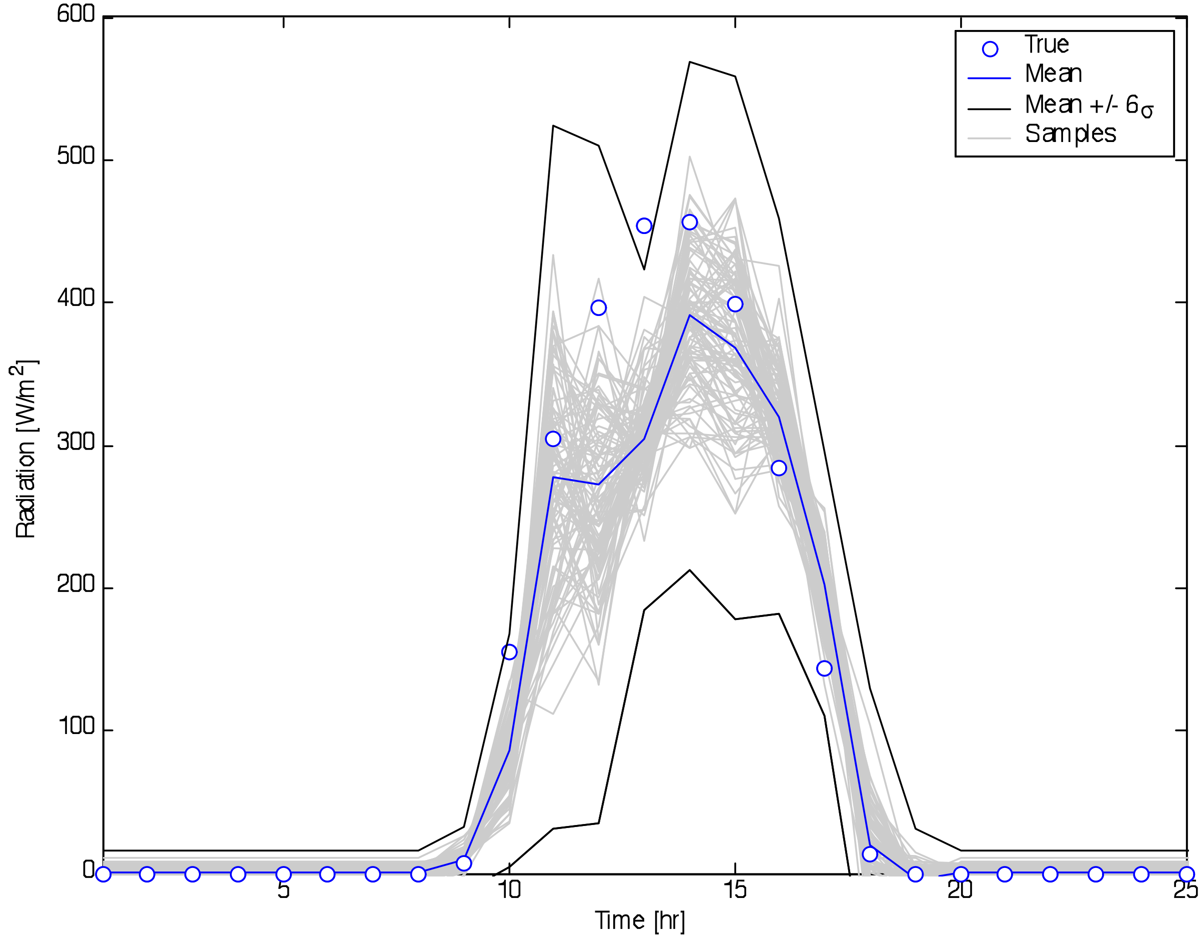
**3. Apply Maximum Likelihood:** $\log p(\mathbf{Y}|\eta) = -\frac{1}{2}\mathbf{Y}\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta)\mathbf{Y} - \frac{1}{2}\log\det(\mathbf{V}(\mathbf{X},\mathbf{X},\eta))$

**4. Posterior Distribution:** $\mathbf{Y}^P = \mathbf{V}(\mathbf{X}^P,\mathbf{X},\eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{Y}$ **Forecast Mean**

$\mathbf{V}^P = \mathbf{V}(\mathbf{X}^P,\mathbf{X}^P,\eta^*) - \mathbf{V}(\mathbf{X}^P,\mathbf{X},\eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{V}(\mathbf{X},\mathbf{X}^P,\eta^*)$ **Covariance**

# Uncertainty Quantification

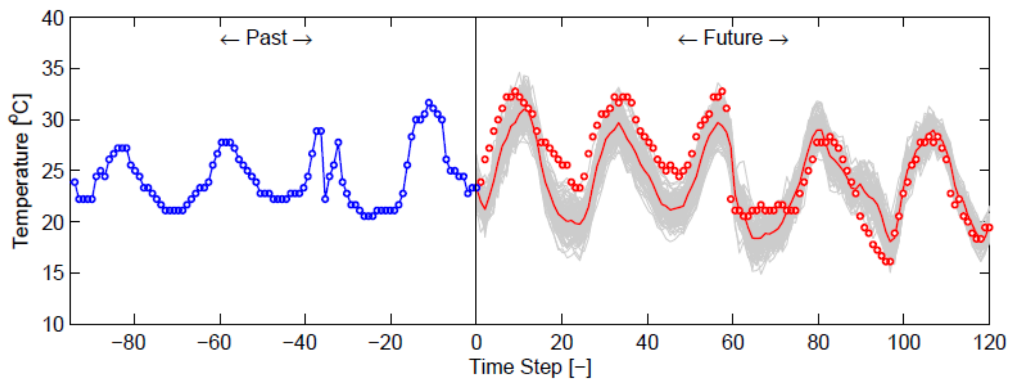
## One-Day Ahead Forecast and Samples from Posterior Distribution



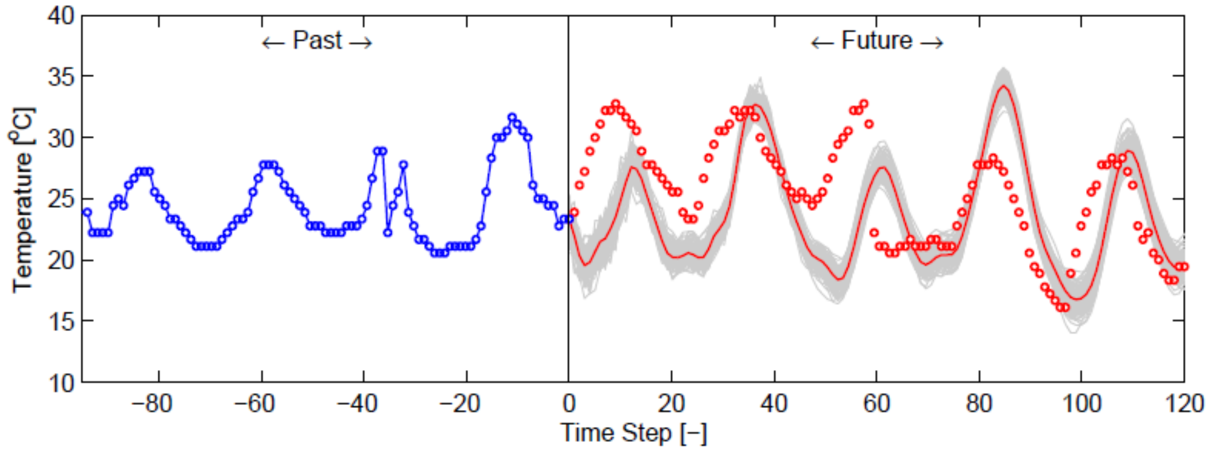

**Covariance Structure *Sort of* Makes Physical Sense, Wide Uncertainty Bounds**

# Uncertainty Quantification

## Ambient Temperature Forecast with GP Modeling *Zavala, A, et.al. 2009*




**One Hour Ahead**




**5 Days Ahead**

**Time-Series Cannot Capture Physical Effects (Spatial), Inconsistent Uncertainty Bounds**

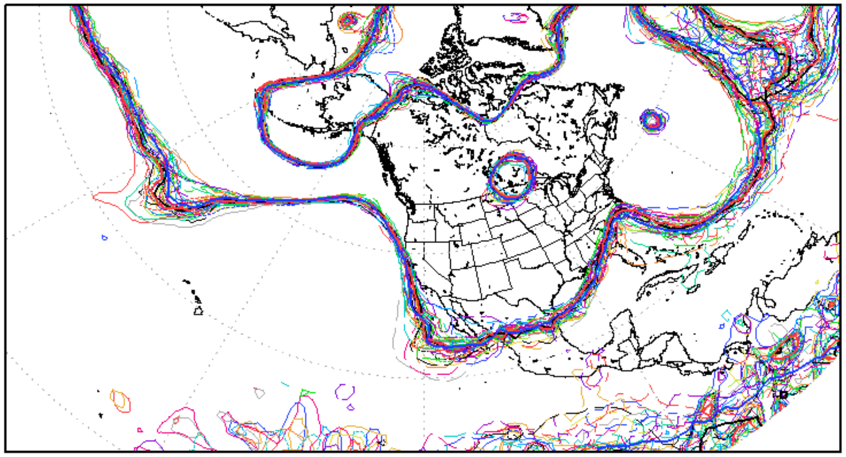
**GP Provides Accurate <u>Interpolations</u> but Poor Extrapolations (e.g. Geostatistics)**

# Uncertainty Quantification

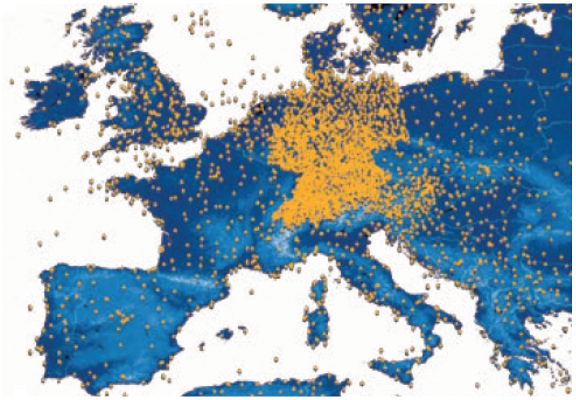
- Advanced Meteorological Models (WRF)
    - Detailed Physico-Chemical Phenomena
    - High Complexity 4-D Fields ($10^6$ States)

- Model <u>Reconciled</u> to Measurements From Multiple Stations

- Reconciliation Techniques:
    - 3-D Var *Courtier, et.al. 1998*
    - 4-D Var (Moving Horizon Estimation) *Navon et.al., 2007*
    - Extended and Ensemble Kalman Filter *Eversen, et.al. 1998*

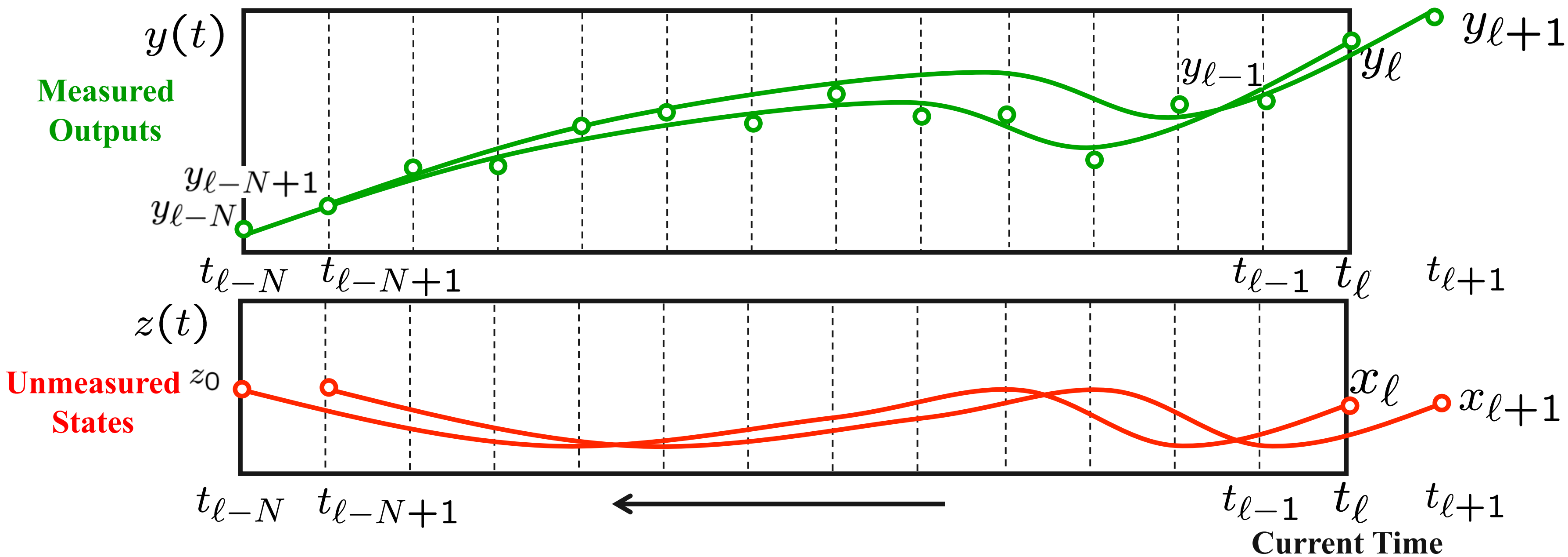


***http://www.emc.ncep.noaa.gov/gmb/ens/***



***http://www.meteomedia.com/***

# 4-D Var and Moving Horizon Estimation

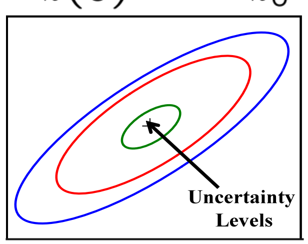



$$\min_{p(t),\,z_0} \sum (y(t_k) - \underline{y_{\ell-k+N}})^T \mathbf{V}_y^{-1} (y(t_k) - y_{\ell-k+N})$$

WRF Model

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}\left(z(t), p(t), u(t)\right) \\ y(t) &= \mathbf{g}(z(t), p(t), u(t)) \\ z(0) &= z_0 \end{aligned}$$

**Uncertain**




$\mathbf{\Pi}_\ell \to 0$

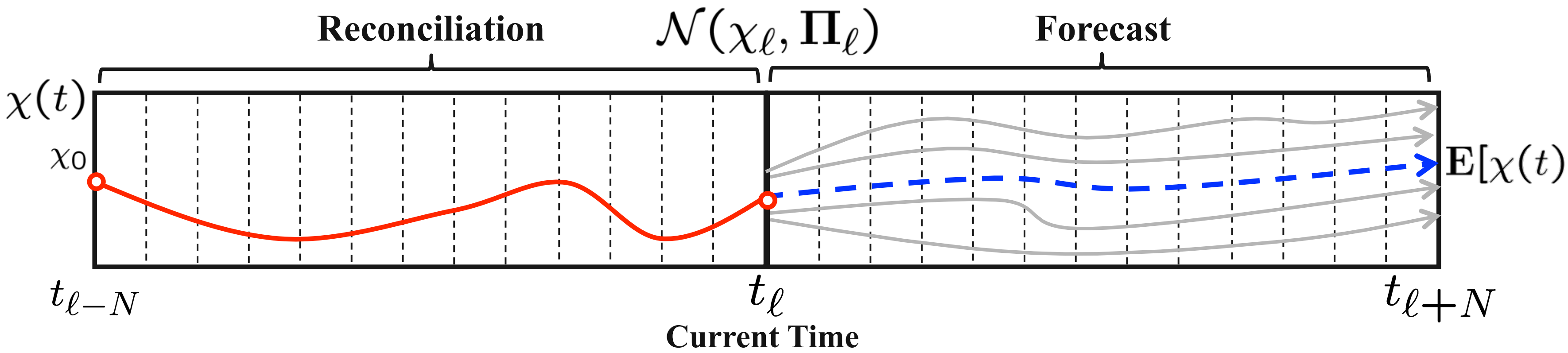
$$\min_{p(t),\,z_0} \sum (y(t_k) - y_{\ell-k+N+1})^T \mathbf{V}_y^{-1} (y(t_k) - y_{\ell-k+N+1})$$

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}\left(z(t), p(t), u(t)\right) \\ y(t) &= \mathbf{g}(z(t), p(t), u(t)) \\ z(0) &= z_0 \end{aligned}$$

**Uncertainty in Current State $x_\ell$ ?**

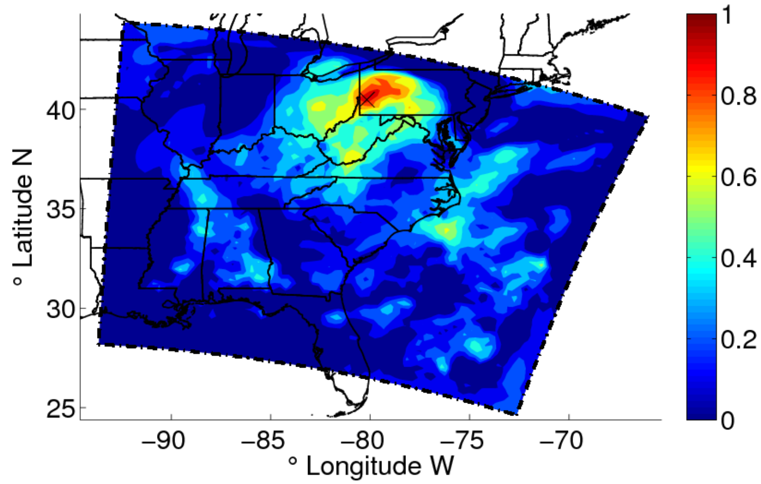
**Needed To Quantify <u>Future</u> Forecast**

# Ensemble Forecast Approach




## Covariance Matrix is Huge ($10^6$ x $10^6$) But …

- **Spatial Correlations Decay <u>Exponentially</u>** *Constantinescu, et.al., 2007*
- **Covariance Can be Approximated Using Gaussian Kernels** *Zavala, Constantinescu & A, 2009*




$$\Pi_{:,i,j} = \exp\left(-\frac{(x_j-x_i)^2+(y_j-y_i)^2}{L_H^2} - \frac{(z_j-z_i)^2}{L_V^2}\right)$$

# Ensemble Forecast Approach

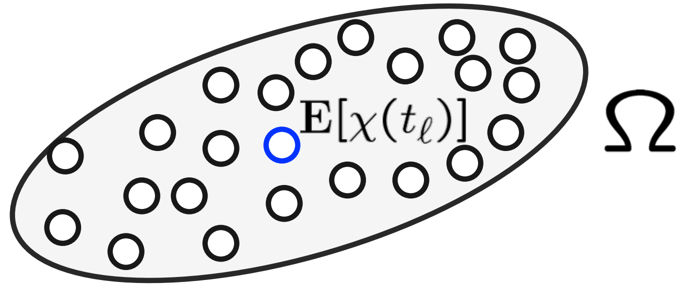
## Ensemble Forecast Approach – Use WRF as Black-Box

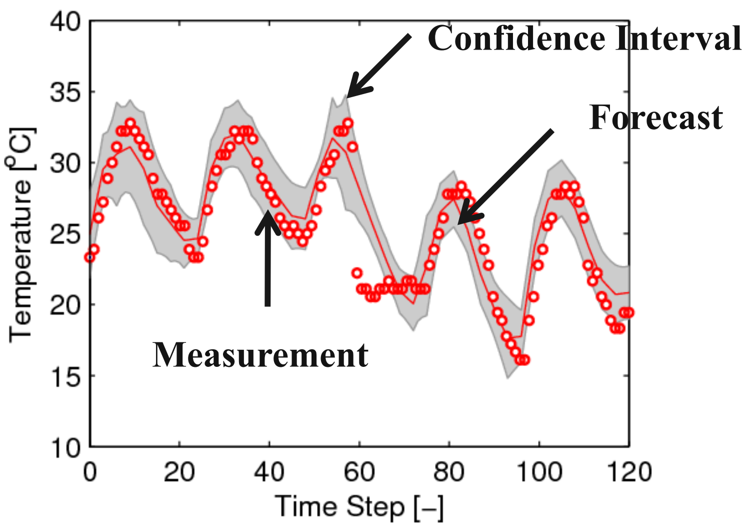
**Propagate Samples of Posterior Through Model**

$$\mathbf{Y}_{[i,j]} := \chi_i(t_{\ell+j}) = \underbrace{\mathcal{M}(\mathcal{M}(...\mathcal{M}}_{j \text{ times}}(\chi_i(t_\ell))))$$

$$\mathbf{E}[\mathbf{Y}] \approx \bar{\mathbf{Y}} := \frac{1}{NS}\sum_{i=1}^{NS} \mathbf{Y}_{[i,:]}$$

$$\mathbf{V} \approx \frac{1}{NS-1}\sum_{i=1}^{NS} (\mathbf{Y}_{[i,:]} - \bar{\mathbf{Y}})(\mathbf{Y}_{[i,:]} - \bar{\mathbf{Y}})^T$$



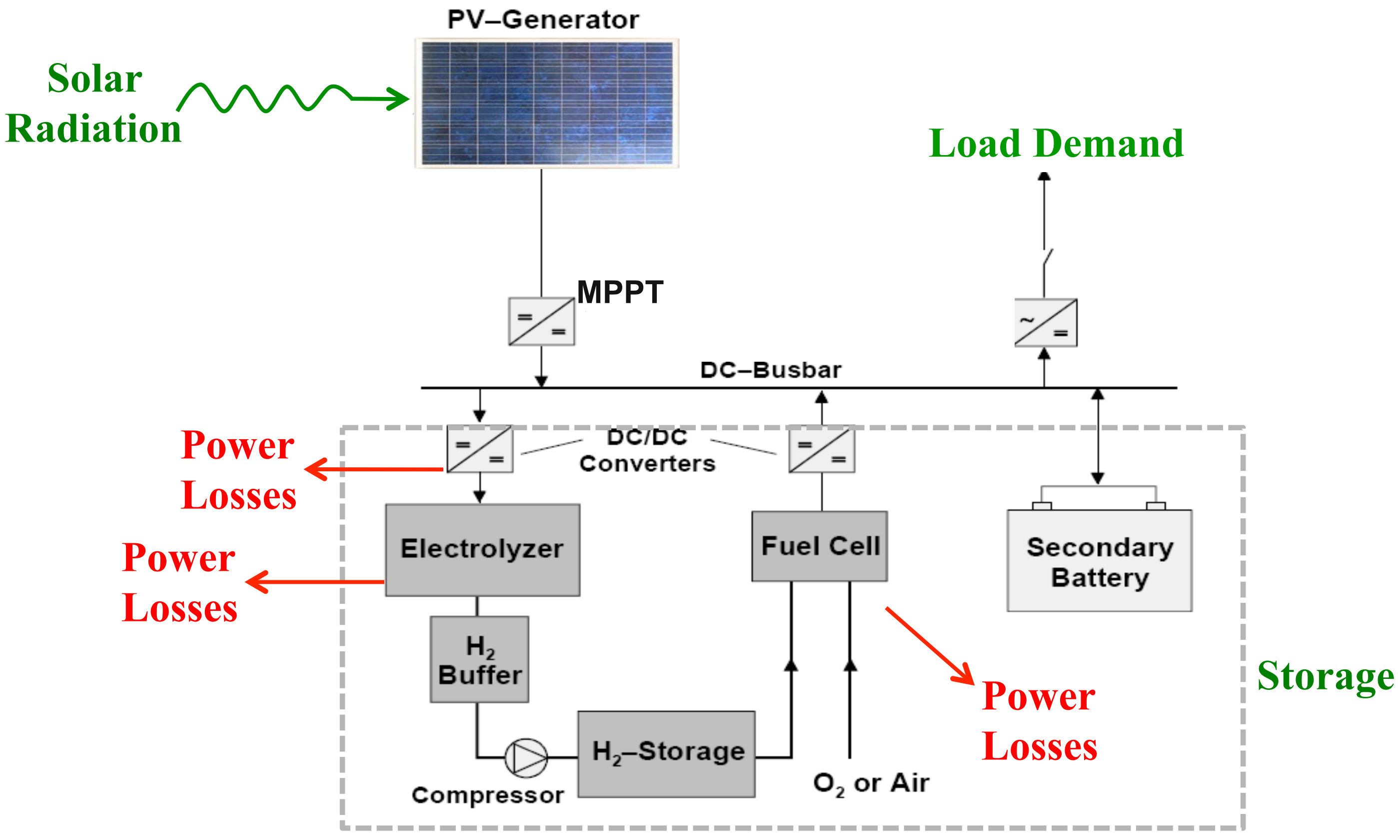

**Hours (August 1st-5th )**

**Validation Results, Pittsburgh Area 2006**

**5 Day Forecast and +/- 3s Intervals**

# Case Studies

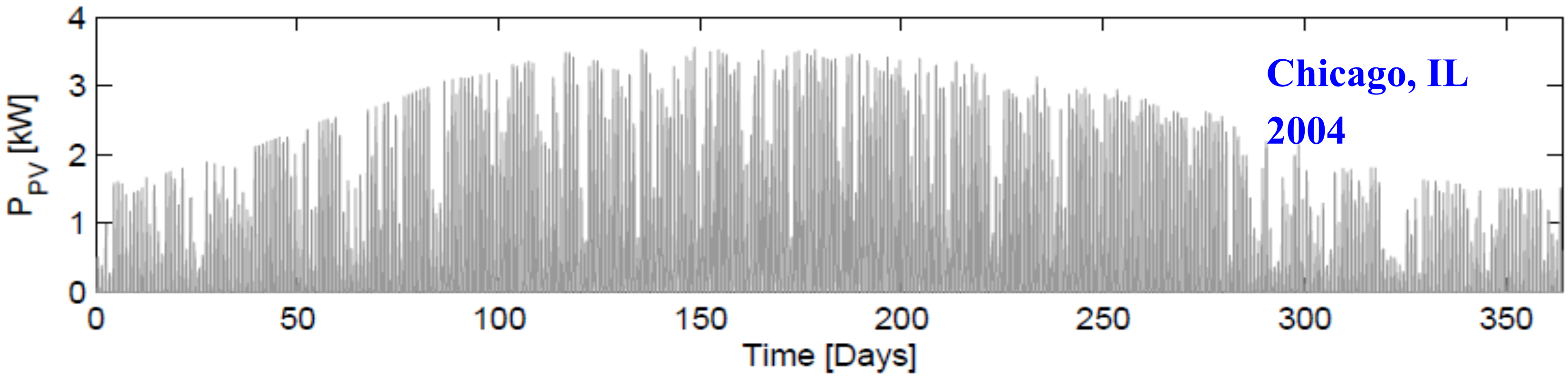
# Hybrid Photovoltaic-$H_2$ System




- **Operating Costs Driven by <u>Uncertain</u> Radiation** *Ulleberg, 2004*
- **Performance Deteriorated by Multiple <u>Power Losses</u>**

# Hybrid Photovoltaic-$H_2$ System

**Effect of Forecast on Economics** *Z., Anitescu, Krause 2009*




**True Future Radiation**

$$\min_{u(t)} \int_{t_\ell}^{t_{\ell+N}} \varphi(z(t), y(t), u(t), \chi(t))dt$$

**Minimize Operating Costs + Maximize $H_2$ Production**

$$\frac{dz}{dt} = \mathbf{f}(z(t), y(t), u(t), \chi(t))$$

$$0 = \mathbf{g}(z(t), y(t), u(t), \chi(t))$$

**Energy Balances**

$$0 \geq \mathbf{h}(z(t), y(t), u(t), \chi(t))$$

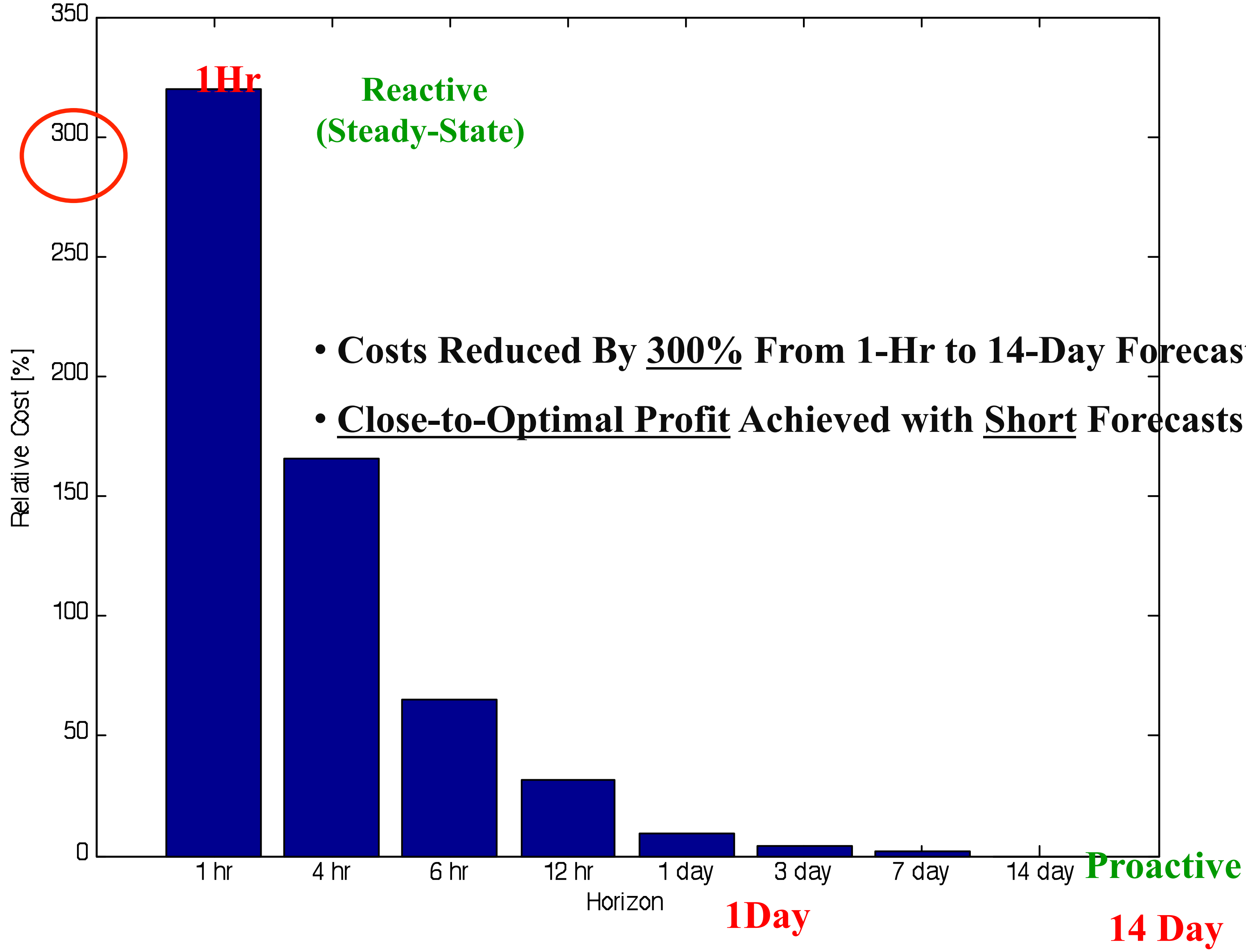
$$z(0) = x_\ell$$

**State-of-Charge, Fuel Cell and Electrolyzer Limits**

- **Forecast Horizon of One Year** – **Highest Achievable Profit**
- **Receding-Horizon with 1hr, 1 Day, …,14 Days Forecast** - **8,700 Problems in Each Scenario**

Argonne NATIONAL LABORATORY

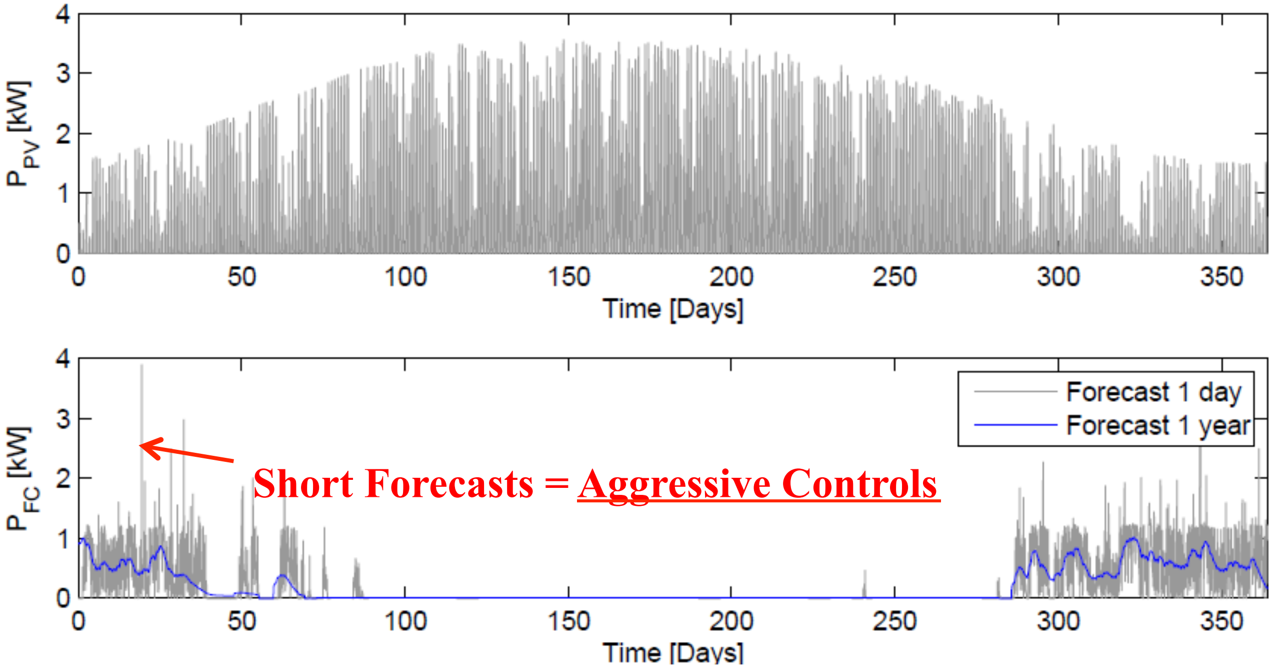
# Hybrid Photovoltaic-$H_2$ System




- Costs Reduced By <u>300%</u> From 1-Hr to 14-Day Forecast
- <u>Close-to-Optimal Profit</u> Achieved with <u>Short</u> Forecasts

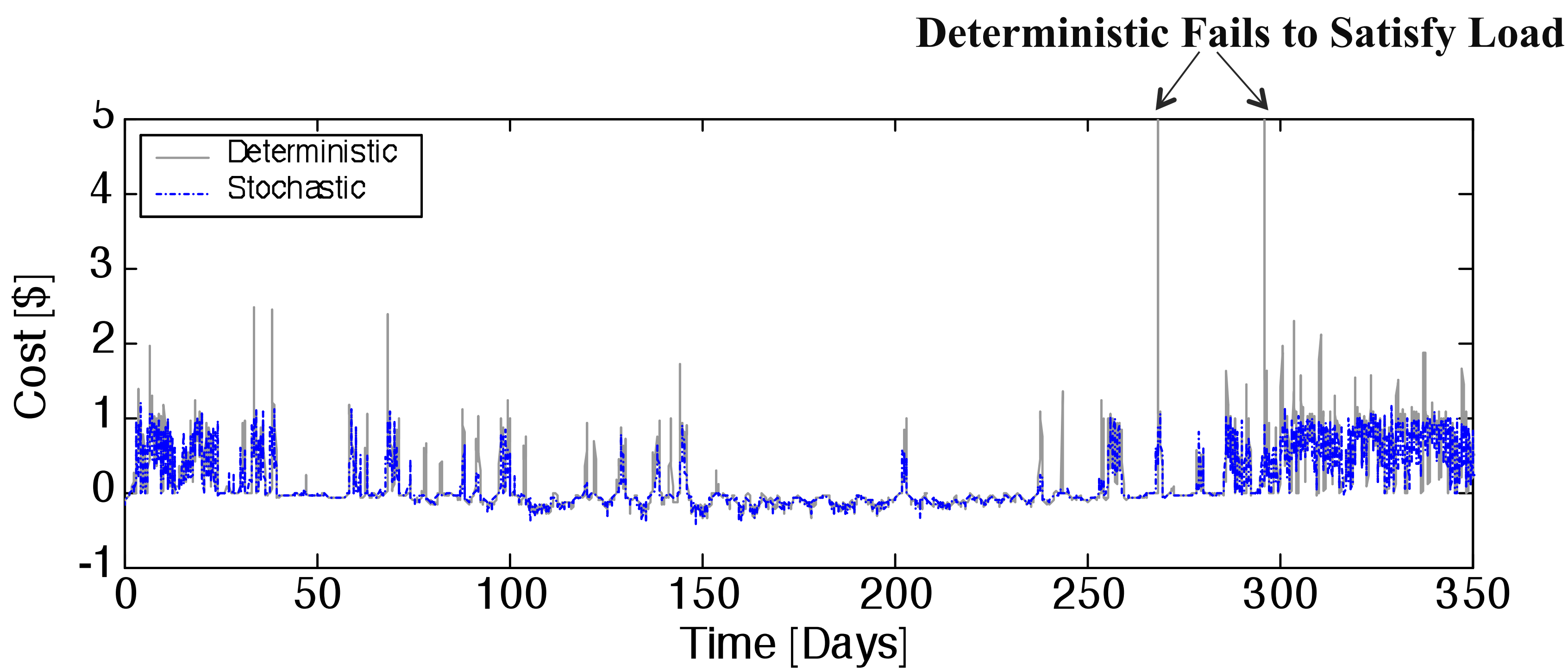
# Hybrid Photovoltaic-$H_2$ System

## Profiles of Fuel Cell Power



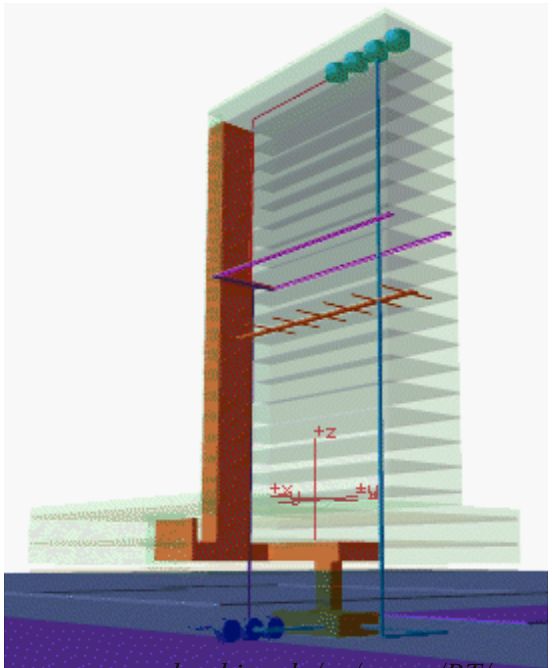
# Hybrid Photovoltaic-$H_2$ System

**Load Satisfaction Deterministic ("Optimization on Mean") vs. Stochastic**




**Handling Stochastic Effects Particularly Critical in <u>Grid-Independent</u> Systems**

# Thermal Management of Building Systems




*www.columbia.edu/cu/gsapp/BT/ LEVER/*

**Minimize Annual Heating and Cooling Costs**

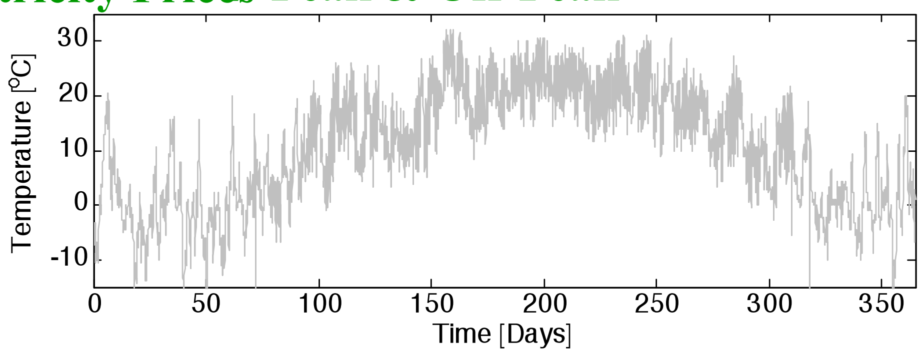
$$\min_{u(t)} \int_{t_\ell}^{t_{\ell+N}} [C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)]\, dt$$

$$\begin{aligned}
C_I \cdot \frac{\partial T_I}{\partial \tau} &= \varphi_h(\tau) - \varphi_c(\tau) - S \cdot \alpha' \cdot (T_I(\tau) - T_W(\tau, 0)) \\
\frac{\partial T_W}{\partial \tau} &= \beta \cdot \frac{\partial^2 T_W}{\partial x^2} \\
\alpha' \left(T_I(\tau) - T_W(\tau, 0)\right) &= -\mathbf{k} \cdot \left.\frac{\partial T_W}{\partial x}\right|_{(\tau,0)} \\
\alpha'' \left(T_W(\tau, L) - T_A(\tau)\right) &= -\mathbf{k} \cdot \left.\frac{\partial T_W}{\partial x}\right|_{(\tau,L)} \\
T_I(0) &= T_I^\ell \\
T_W(0, x) &= T_W^\ell(x)
\end{aligned}$$

**Energy Balances**

**NLP with 100,000 Constraints & 20,000 Degrees of Freedom**

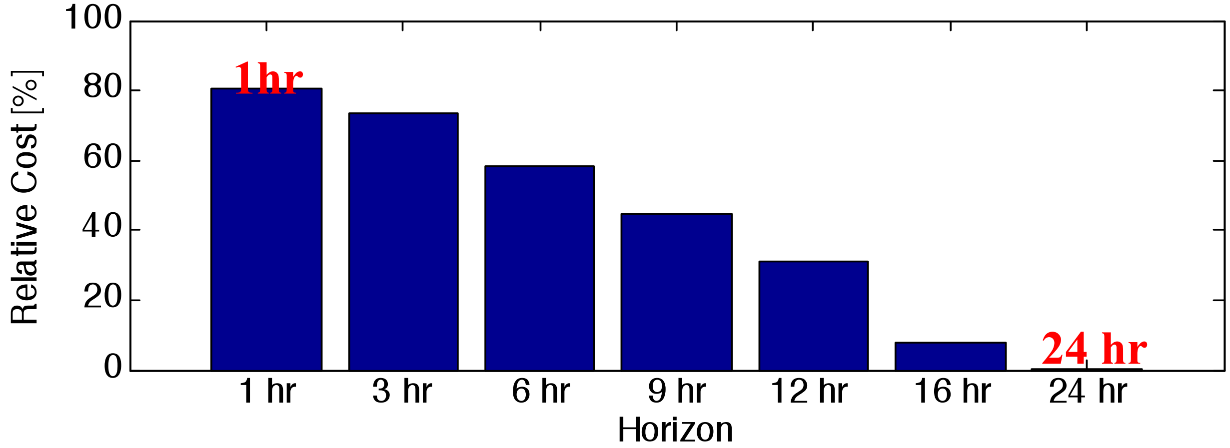
**Time-Varying Electricity Prices → Peak & Off-Peak**



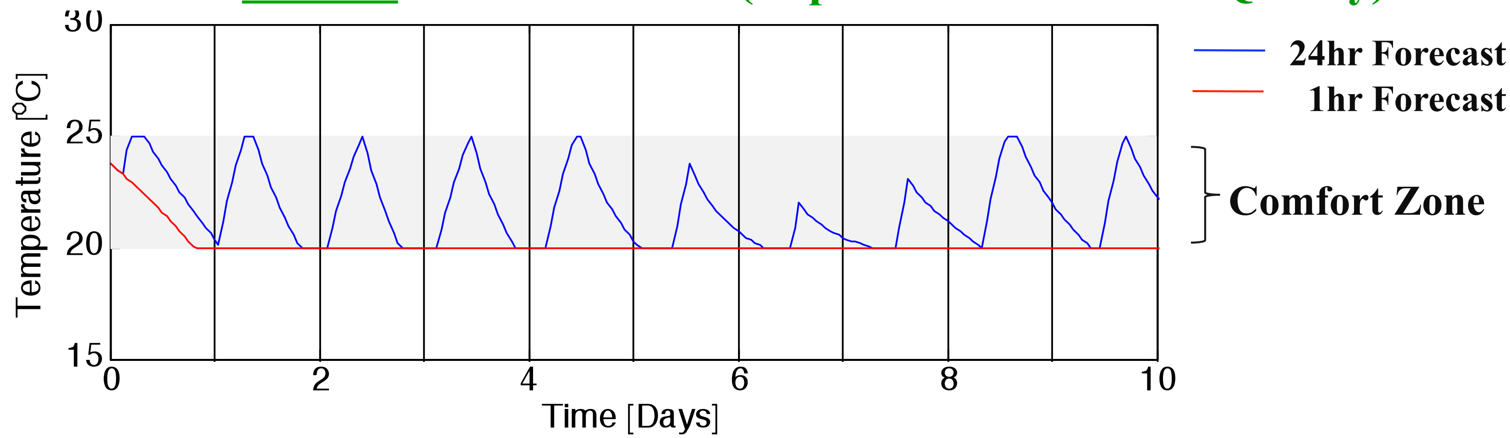

**Pittsburgh, PA 2006**

# Thermal Management of Building Systems

## Effect of Forecast on Energy Costs



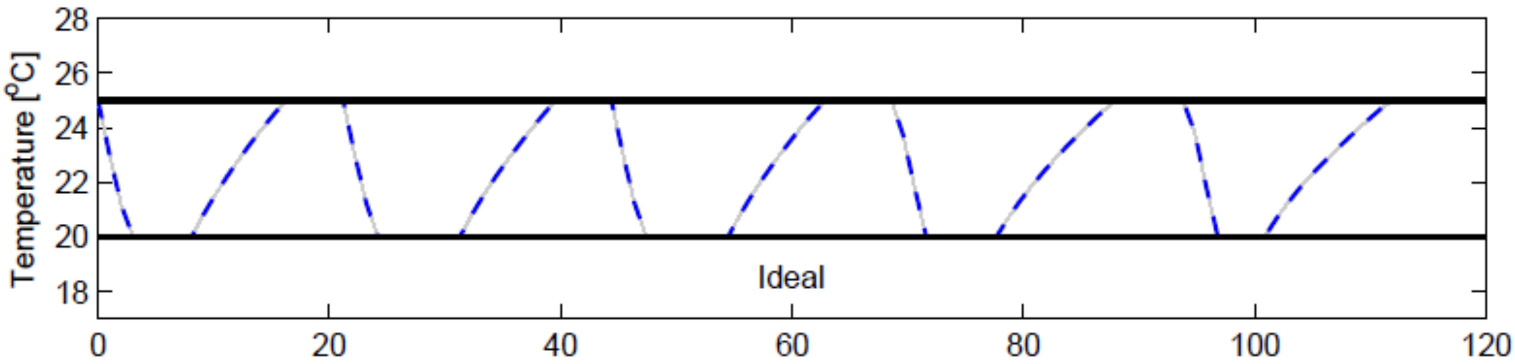

## Forecast Leads to 20-80% Cost Reduction (Depends on Insulation Quality)




## Exploit Comfort Zone and Weather Info to Heat/Cool when Cheaper *Braun, 1990*

# Thermal Management of Building Systems

## Performance Optimizer using WRF and GP Model Forecasts




**Perfect Forecast**

# Conclusions and Future Work

# Conclusions and Future Work

## Integrative Study of Weather Forecast-Based Optimization

WRF Model + Ensemble Approach + Stochastic Receding-Horizon

Important Economic Benefits, Niche Market is Huge

New Algorithms and Formulations Needed

- We showed that stochastic formulation matters (deterministic results in big losses).
- We showed that weather forecast inclusions results in 20-80% cost reduction
- Weather uncertainty is a hard, important, problem that data-only methods (such as GP) are unlikely to crack

## Future and On-Going Work

Convergence of SAA Approximations for Stochastic Receding-Horizon

Variance Reduction Control Formulations

Integration Gaussian Process + WRF Forecasts

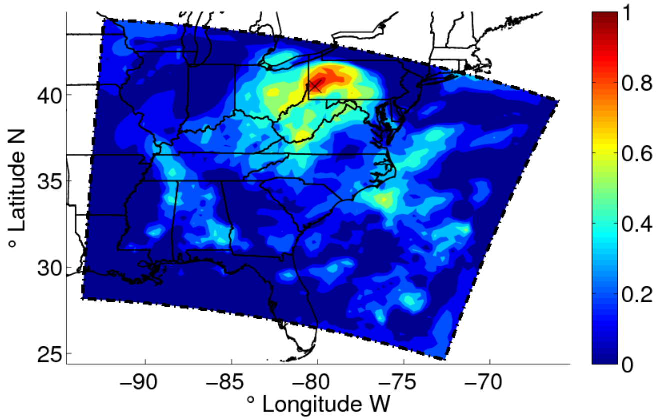
# Conclusions and Future Work

## Integrative Study of Weather Forecast-Based Optimization

- WRF Model + Ensemble Approach + Stochastic Receding-Horizon
- Important Economic Benefits, Niche Market is Huge
- New Algorithms and Formulations Needed

## Future and On-Going Work

- Convergence of SAA Approximations for Stochastic Receding-Horizon
- Variance Reduction Control Formulations
- Integration Gaussian Process + WRF Forecasts




WRF Model Provides Coarse Forecasts
(Km, Hour Scales)
Gaussian Process Model to Create
High-Fidelity Forecasts
(Meters, Minutes)

# Collaborators

**Dr. Victor Zavala, Mathematics-Argonne**

**Dr. Emil Constantinescu, Mathematics-Argonne**

**Dr. Ted Krause, Chemical Technology-Argonne**

# Weather Forecast-Based Optimization of Industrial Systems


**Victor M. Zavala**

Postdoctoral Researcher
Mathematics and Computer Science Division
Argonne National Laboratory

*vzavala@mcs.anl.gov*


**PSE Seminar, University of Wisconsin**
**Madison, WI**
**March 30th, 2009**

THE UNIVERSITY OF TEXAS AT AUSTIN

Argonne NATIONAL LABORATORY

# Weather Forecast-Based Optimization of Integrated Energy Systems


**Victor M. Zavala**

Postdoctoral Researcher
Mathematics and Computer Science Division
Argonne National Laboratory

*vzavala@mcs.anl.gov*


**PSE Seminar, University of Wisconsin**
**Madison, WI**
**March 30th, 2009**

THE UNIVERSITY OF TEXAS AT AUSTIN

Argonne NATIONAL LABORATORY